1. Methodology Document

Model Methodology Document

Introduction

This document outlines the methodology developed for credit scoring Compound V2 protocol wallets. The model assigns scores ranging from 0 to 100 to each wallet based on their transaction behavior, where higher scores indicate reliable and responsible usage patterns and lower scores suggest risky, bot-like, or exploitative behaviors.

Data Processing Approach

Data Selection and Loading

- Selected the three largest files from the Compound V2 dataset to ensure comprehensive coverage
- Processed raw JSON data to extract transaction-level information grouped by wallet addresses
- Organized transactions by type (deposit, borrow, repay, withdraw, liquidation)

Feature Engineering

The model extracts the following key features from raw transaction data:

1. **Basic Transaction Metrics**
    - Transaction counts (total, by type)
    - Transaction volume in USD (total, by type)
    - Unique assets used

2. **Repayment Behavior**
    - Repay ratio: `total_repay_usd / total_borrow_usd`
    - Repay-to-borrow count ratio: `len(repays) / len(borrows)`
3. **Risk Indicators**
    - Liquidation ratio: `total_liquidated_usd / total_borrow_usd`
    - Borrow-deposit ratio: `total_borrow_usd / total_deposit_usd`
    - Withdraw-deposit ratio: `total_withdraw_usd / total_deposit_usd`
4. **User Behavior Patterns**
    - Account age (days from first to last transaction)
    - Transaction frequency (transactions per day)
    - Average time between transactions
    - Standard deviation of time between transactions
    - Time consistency (coefficient of variation in transaction timing)
    - Amount volatility (standard deviation / mean of transaction amounts)
    - Days since last transaction
5. **Asset Utilization**
    - Asset diversity (unique asset count)
    - Asset-specific transaction counts

Scoring Model Design

The credit scoring model combines multiple components with specific weightings:

1. Repayment Behavior (30% of score)

```
repayment_score = 30 * (
    1.0 if repay_ratio > 0.95 else
```

```
    0.8 if repay_ratio > 0.8 else
    0.6 if repay_ratio > 0.6 else
    0.4 if repay_ratio > 0.4 else
    0.2 if repay_ratio > 0.2 else
    0
)
```

2. Liquidation Risk (25% of score)

```
liquidation_score = 25 * (1 - min(liquidation_ratio / 5, 1))
```

3. Account Stability (15% of score)

```
stability_score = 15 * (
    1.0 if account_age_days > 180 else
    0.8 if account_age_days > 90 else
    0.6 if account_age_days > 30 else
    0.4 if account_age_days > 7 else
    0.2
)
```

4. Transaction Patterns (15% of score)

Penalties applied for:

- Bot-like behavior (high frequency, low timing variance): -0.8
- High borrowing risk (high borrow-deposit ratio): -0.4
- High withdrawal risk (high withdraw-deposit ratio): -0.2

5. Asset Diversity (15% of score)

```
diversity_score = 15 * (
    1.0 if unique_assets > 4 else
    0.7 if unique_assets > 2 else
    0.4 if unique_assets > 1 else
    0.2
)
```

Anomaly Detection

The model employs Isolation Forest to identify wallets with anomalous transaction patterns:

- Uses transaction counts, volume metrics, ratios, and timing features
- Applies 50% score penalty to anomalous wallets
- Contamination parameter set to 0.05 (assuming 5% of wallets exhibit anomalous behavior)

Rationale for Scoring Components

1. **Repayment Behavior (30%)**: The primary indicator of credit-worthiness is whether a borrower repays their loans. Higher repayment ratios strongly indicate responsible borrowing behavior.
2. **Liquidation Risk (25%)**: Liquidations indicate inadequate collateralization and risk management. Wallets with no or minimal liquidations demonstrate better protocol interaction.
3. **Account Stability (15%)**: Longer-term users demonstrate commitment to the protocol and typically understand its mechanisms better than newer users.
4. **Transaction Patterns (15%)**: Abnormal transaction patterns may indicate bots, exploits, or high-risk

strategies. Consistent, human-like transaction patterns receive higher scores.

5. **Asset Diversity (15%)**: Using multiple assets indicates a more sophisticated understanding of the protocol and typically suggests legitimate usage rather than opportunistic exploitation.

Score Calculation and Normalization

The final credit score is calculated as:

```
credit_score = repayment_score + liquidation_score +
stability_score + transaction_pattern_score + diversity_score
```

The score is then:

1. Adjusted for anomalous behavior (50% penalty if detected as anomalous)
2. Clipped to ensure it remains in the 0-100 range
3. Rounded to the nearest integer

Potential Future Improvements

Spatial-Temporal Graph Neural Networks (STGNNs)

Integrating STGNNs could enhance the model's ability to detect complex transaction patterns by analyzing both wallet relationships (spatial) and behavioral evolution over time (temporal). This approach models wallets as nodes and transactions as directed edges with timestamps, enabling the detection of suspicious activity like circular transfers or sudden liquidity shocks.

Privacy-Preserving Federated Learning

Adopting federated learning with blockchain-based aggregation would allow secure model updates across institutions without sharing raw wallet data. Each participant (e.g., lending protocols) trains a local model on their user transactions, with updates consolidated via smart contracts. This preserves privacy while improving coverage of rare fraud patterns-critical in decentralized finance.

Adversarial Validation for Concept Drift

Implementing adversarial validation would automatically detect shifts in transaction patterns caused by market volatility or new attack vectors. A classifier trained to distinguish recent vs historical transactions identifies features with diverging distributions (e.g., sudden changes in collateralization ratios).